

A ROBUST MULTI-SENSOR DEEP REGRESSION FRAMEWORK FOR PREDICTIVE PLANT GROWTH MODELLING IN CONTROLLED ENVIRONMENTS

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ABSTRACT

The analysis of plant growth and development in controlled agricultural environments has become increasingly important to ensure sustainable and efficient food production. Traditionally, plant monitoring relied on manual observations and basic statistical approaches, which provided limited insights into the complex interactions between environmental factors and plant physiology. To address these challenges, this study proposes a machine learning-driven analytical framework designed for comprehensive plant development analysis. The system integrates data preprocessing, exploratory data analysis, classification, regression, and hybrid deep learning approaches within a unified pipeline. Classification algorithms such as Support Vector Classifier (SVC), Bernoulli Naive Bayes (BNC), and Multinomial Naive Bayes (MNC) are employed to identify plant growth stages. Regression models, including Decision Tree Regressor (DTR), Support Vector Regressor (SVR), and Ridge Regressor (RR), are utilized to estimate growth-related parameters. Furthermore, two hybrid models are introduced to enhance predictive performance. The Deep Feature Probabilistic Classifier (DFPC) combines Feed Forward Neural Networks (FFNN) with Gaussian Naive Bayes (GNB) for improved classification accuracy, while the Hybrid Deep Ridge Predictor (HDRP) integrates FFNN with Ridge Regressor to achieve precise regression outcomes. Experimental results demonstrate that the DFPC model attains an accuracy of 94.42%, whereas the HDRP model achieves an R^2 score of 0.999. These findings highlight the effectiveness of combining deep learning and machine learning techniques for accurate plant growth analysis and informed decision-making in controlled agricultural systems.

Keywords: Agriculture analytics, classification, deep learning, plant growth, regression, sensor data

1. Introduction

Crop yield is fundamentally influenced by the growth and differentiation of crops, along with the distribution and accumulation of photosynthetic products, making it a critical focus in crop science. Accurate and early prediction of crop yield remains one of the key research areas in precision agriculture [1]. Oilseed rape (*Brassica napus* L.) is an important global oilseed crop, widely utilized for producing high-quality animal feed, edible oil,

culinary products, biodiesel, and more [2,3]. Timely and precise yield estimation of oilseed rape plays a crucial role in enabling agricultural producers to effectively plan cultivation, breeding, production, and marketing activities. Traditional methods for crop yield estimation primarily relied on establishing relationships between agronomic or climatic variables and crop yield through manual surveys or statistical analysis techniques [4,5]. However, these approaches lacked consistency and were often

time-consuming and labor-intensive. With the expansion of large-scale commercial breeding of oilseed rape, there has been a significant increase in the diversity of breeding materials, making it challenging to maintain data uniformity and timeliness for yield estimation.

Consequently, there is a pressing need to develop rapid, reliable, and non-destructive methods for accurate yield prediction at the field scale. Remote sensing has emerged as an effective real-time approach for acquiring crop phenotypic information, offering extensive coverage and minimal crop disturbance, thereby becoming widely adopted in agricultural data collection [4]. The increasing demand for timely and non-invasive crop yield assessment across different scales has further accelerated the adoption of remote sensing technologies [5]. In particular, the use of unmanned aerial vehicles (UAVs) has addressed many limitations associated with satellites, aircraft, and ground-based systems. UAVs support frequent and flexible data acquisition at specific locations and times, enabling crop monitoring through multi-scale and multi-temporal imaging. This facilitates detailed observation of fine-scale spatial patterns in a more efficient and practical manner.

Research Motivation: The increasing global demand for food security, coupled with the limitations of conventional farming techniques, motivates the development of intelligent greenhouse management systems. By leveraging machine learning algorithms, it becomes possible to analyse large-scale agricultural datasets and derive meaningful insights that would otherwise remain hidden. This research is inspired by the need to reduce resource wastage, improve yield predictability, and optimize agricultural practices in greenhouse environments. Furthermore, the integration of hybrid deep learning and statistical models provides a unique

opportunity to enhance prediction accuracy beyond what individual algorithms can achieve.

2. Literature Survey

Zhu H et al. [6] explored different machine learning algorithms, i.e., multiple linear regression (MLR), partial least squares regression (PLSR), least squares support vector machine (LS-SVM), back propagation neural network (BPNN), extreme learning machine (ELM), and radial basis function neural network (RBFNN), were developed and compared. With multi-source data fusion by combining vegetation indices (colour and narrow-band VIs), robust prediction models of yield in oilseed rape were built. Balan T et al. [7] described a multi-sensor system for agriculture consisting of a soil probe, an air probe and a smart data logger. Furthermore, they focused on the analytics and decision support system implementation that provides farming recommendations and is enhanced with a feedback loop from farmers and a social trust index that will increase the reliability of the system.

Fei S et al. [8] studied on multi-sensor data fusion and ensemble learning for grain yield prediction in wheat. A set of thirty wheat cultivars and breeding lines were grown under three irrigation treatments i.e., light, moderate and high irrigation treatments to evaluate the yield prediction capabilities of a low-cost multi-sensor (RGB, multi-spectral and thermal infrared). Manuelito C et al. [9] evaluated the effectiveness of two sensor-based approaches—proximal sensing with a FLAME spectrometer and remote sensing via UAV-mounted multispectral imaging—compared with foliar chemical analyses as the reference standard, for diagnosing the nutritional status of olive trees.

Xu R et al. [10] designed the multi-sensor unmanned aerial system was open sourced. A data processing pipeline was proposed to preprocess the raw data and to extract

phenotypic traits at the plot level, including morphological traits (canopy height, canopy cover, and canopy volume), canopy vegetation index, and canopy temperature. Lee D-H et al. [11] developed using high-resolution RGB, multispectral (MSP), and thermal infrared (TIR) imagery collected throughout the 2020 growing season. The imagery was used to extract various vegetation indices, crop features (vegetation fraction, crop height model), and a water stress indicator (CWSI). The deep neural network (DNN) model consistently outperformed support vector machine (SVM) and random forest (RF) models Grunwald S et al. [12] collected DSC sensor data and spatially co-located soil cores that were sliced into narrow layers for laboratory-based soil measurements. Partial Least Squares Regression (PLSR) cross-validation was used to compare the results of testing four data integration methods.

Chi Z et al. [13] proposed a new method for forest age estimation that integrates multi-source remote-sensing data with machine learning. The employs the Continuous Degradation Detection (CODED) algorithm combined with spectral unmixing models and Normalized Difference Fraction Index (NDFI) time series analysis to update forest disturbance information and provide annual forest distribution, mapping young forest distribution. Jin X-B et al. [14] overcome the traditional deep learning network's over-fitting to the sensor noise, the Bayesian method is used to obtain the weight distribution characteristics of the sub-predictor network. A multi-layer perceptron (MLP) is constructed as the fusion layer to fuse the results from different sub-predictors. The experiments were implemented to verify the effectiveness of the proposed method by meteorological data from Beijing.

Roy AM et al. [15] proposed a model that has been improved to optimize for both detection speed and accuracy and applied to multi-class apple plant disease detection in the real

environment. The mean average precision (mAP) and F1-score of the detection model reached up to 91.2% and 95.9%, respectively, at a detection rate of 56.9 FPS. The overall detection result demonstrates that the current algorithm significantly outperforms the state-of-the-art detection model with a 9.05% increase in precision and 7.6% increase in F1-score. They proposed model can be employed as an effective and efficient method to detect different apple plant diseases under complex orchard scenarios. Qaisar I et al. [16] presented an occupancy prediction Transformer network (OPTnet). They fused and fed multi-sensor data (building occupancy, indoor environmental conditions, HVAC operations) into a Transformer model to forecast the future occupancy presence in multiple zones.

Balan T et al. [17] proposed a Smart agriculture based on new types of sensors, data analytics and automation, is an important enabler for optimizing yields and maximizing efficiency to feed the world's growing population while limiting environmental pollution. The aim was to describe a multi-sensor Internet of Things (IoT) system for agriculture consisting of a soil probe, an air probe and a smart data logger. Song L et al. [18] developed a multi-sensor based variable spray system, where a Bang-Bang relay controller is used to speed up the system operation, and adaptive fuzzy nonlinear PID is employed to improve the accuracy and stability of the system. With the chaotic optimization of controller parameters, the system is globally optimized in the whole solution space. Sreenivas Pratapagiri et al. [19] proposed a plant leaf disease detection system using the Convolutional Neural Network (CNN). The model extracted visual features from leaf images. The system classified diseases accurately for early agricultural intervention.

3. Proposed Methodology

The proposed methodology establishes a well-defined framework for analyzing multi-sensor agricultural data to study plant development and environmental impacts within controlled environments. As illustrated in Fig. 2, the process initiates with dataset acquisition, followed by preprocessing and exploratory data analysis. Subsequently, analytical models are applied for both classification and regression tasks. These models utilize environmental and plant growth features to determine developmental stages and predict growth parameters. The framework combines conventional machine learning approaches with hybrid deep learning models to enhance prediction accuracy and robustness. Neural networks are employed for feature extraction to capture complex nonlinear relationships among variables, while probabilistic and regression algorithms are used for final predictions. A graphical user interface allows users to upload datasets, perform preprocessing, train models, visualize outputs, and generate predictions. Efficient data handling and visualization techniques facilitate better interpretation of feature relationships, while continuous evaluation and retraining enable adaptability to new sensor data.

User Interface (Tkinter Application)

- The system is accessed through a desktop-based graphical interface developed using Tkinter.
- It supports key operations such as user authentication, dataset upload, preprocessing, model training, EDA visualization, and result generation.
- All functionalities are executed via Graphical User Interface (GUI) controls, which interact with internal processing modules.
- The interface also serves as the primary medium for displaying predictions, results, and analytical insights.

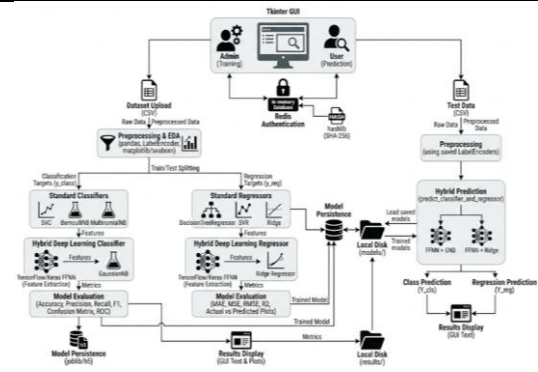


Fig. 2: Proposed system architecture.

Authentication System (Redis Storage)

- A secure authentication mechanism is implemented with role-based access (Admin and User).
- User credentials are protected using hashed storage within a Redis database.
- This ensures that only authorized users can access sensitive analysis and prediction features.

Dataset Input (CSV Sensor Data)

- The system accepts CSV files containing multi-sensor agricultural data as input.
- The dataset includes environmental and plant-related attributes such as root weight and vegetative growth metrics.
- Once uploaded through the interface, the data is directed to the preprocessing stage.

Data Preprocessing and Feature Engineering

- Raw data is cleaned by removing irrelevant columns and handling missing values.
- Categorical attributes are transformed into numerical representations using Label Encoding.
- The processed output is a structured feature set suitable for model training.

Exploratory Data Analysis (EDA)

- Provides insights into data distribution and relationships among variables.
- Generates visualizations such as count plots, box plots, violin plots, and correlation heatmaps.
- Helps identify patterns, feature importance, and anomalies before model training.

Existing Baseline Classification Models

- Preprocessed data is first evaluated using traditional classification algorithms:
 - **SVC:** Separates classes using hyperplane-based decision boundaries.
 - **BNB:** Applies probabilistic classification based on feature presence.
 - **MNB:** Utilizes frequency-based feature distributions.
- These models classify plant development stages such as SA, SB, SC, TA, TB, and TC.

Proposed DFPC

- The hybrid classification model consists of two components:
 - **FFNN:** Extracts high-level nonlinear features from sensor data through multiple hidden layers.
 - **GNB:** Uses the extracted features for probabilistic classification to improve accuracy and reliability.

Existing Baseline Regression Models

- Used to predict continuous plant growth parameters:

- **DTR:** Employs tree-based decision rules.
- **SVR:** Uses margin-based optimization for regression.
- **RR:** Applies L2 regularization for stable predictions.

Proposed HDRP

- The hybrid regression model operates in two stages:
 - **FFNN:** Performs deep feature extraction from sensor inputs.
 - **Ridge Regressor:** Uses the extracted features to predict growth parameters such as PHR with improved stability.

Prediction Output and Results

- The system produces two types of outputs:
 - **Classification:** Identifies plant development stages.
 - **Regression:** Predicts numerical growth values.
- Results are displayed through the Tkinter interface for user interpretation.

Model Evaluation and Performance Metrics

- **Classification Performance:** Measured using Accuracy, Precision, Recall, and F1-score.
- **Regression Performance:** Evaluated using MAE, MSE, RMSE, and R^2 score.
- These metrics validate the effectiveness of both baseline and proposed models.

Model Retraining and Adaptive Learning

- The framework supports continuous learning by incorporating new sensor data.

- Administrators can upload updated datasets to retrain models.
- This ensures adaptability to changing environmental conditions and sustains prediction accuracy.

3.1 Hybrid Deep Ridge Predictor

The HDRP is a regression framework designed to estimate plant growth values by combining deep learning feature extraction with regularized regression techniques. In this approach, environmental sensor features are first processed through a neural network to learn complex patterns and relationships present in the dataset. The neural network transforms the original input data into deep feature representations that capture important growth-related characteristics. These extracted features are then provided to a Ridge regression model, which performs the final prediction of plant growth indicators. By integrating deep feature extraction with regularized regression, this hybrid approach improves prediction accuracy, stability, and generalization when analysing multi-sensor agricultural data as shown in Figure 3.

Input Feature Preparation: The regression process begins with the processed dataset obtained after preprocessing and exploratory analysis stages. The dataset contains environmental sensor attributes and plant growth indicators that serve as input variables for the regression model. These structured numerical features are organized into feature vectors suitable for computational analysis.

Deep Feature Extraction using Neural Network: The prepared feature vectors are passed through a feed-forward neural network composed of several hidden layers. Each layer processes the input data and extracts deeper representations of the relationships between environmental factors and plant growth behaviour. Through multiple transformations, the neural network captures complex nonlinear patterns in the dataset.

Generation of Deep Feature Representation:

After passing through the hidden layers, the neural network produces a compact deep feature representation from its intermediate layer. This representation highlights the most informative characteristics of the input dataset while reducing irrelevant variations. The resulting deep feature vectors become the input for the regression prediction stage.

Ridge Regression Prediction: The extracted deep features are forwarded to a Ridge regression model for final prediction. Ridge regression applies linear regression with L2 regularization to minimize prediction error while controlling model complexity. This regularization helps prevent overfitting and ensures stable predictions across different data samples.

Final Growth Prediction Output: After the Ridge regression model processes the deep feature vectors, it generates predicted numerical values representing plant growth indicators. These predictions estimate the growth parameter based on the environmental conditions recorded by the sensors. The predicted values are then used for performance evaluation and further analysis within the analytical system.

This hybrid regression model combines the feature extraction power of a Feedforward Neural Network with the regularization benefits of Ridge Regression. The FFNN captures complex patterns from sensor data, and Ridge Regression predicts PHR while preventing overfitting.

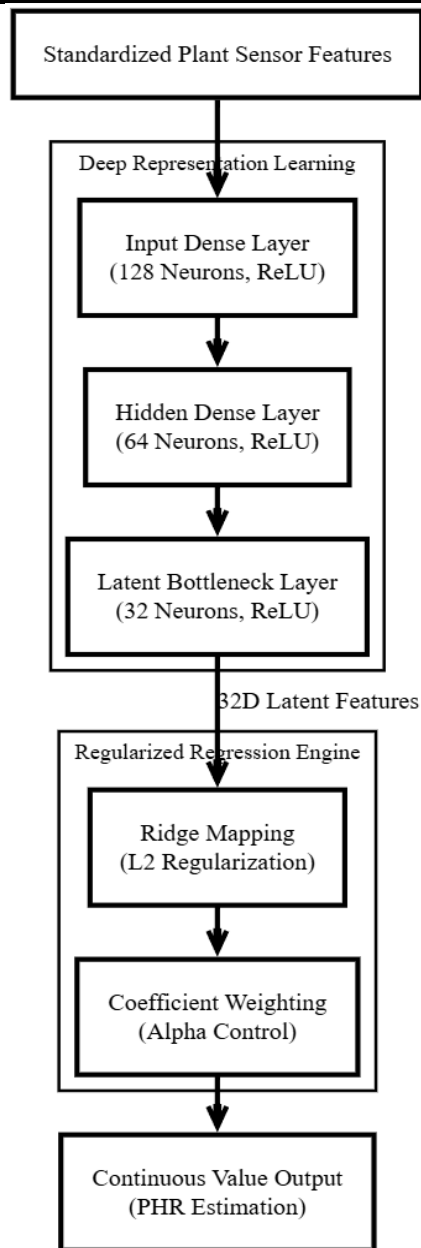


Fig. 3: Internal workflow of HDRP.

4. Results and Discussions

Figure 4 presents a comprehensive exploratory data analysis (EDA) of the dataset, highlighting class distribution, feature variability, and inter-feature relationships. The class label distribution plot indicates a balanced dataset, as all encoded classes (0–5) exhibit nearly equal sample counts, ensuring that the model training process is not biased toward any specific class. The boxplot of average dry weight of roots (ADWR) across classes reveals distinct

variations, with certain classes (e.g., class 2) showing higher median values and wider dispersion, suggesting stronger root development, while others (e.g., class 3 and 4) exhibit lower and more compact distributions. The correlation heatmap provides insights into linear dependencies among features, where moderate positive and negative correlations can be observed between attributes such as plant height, leaf area, and biomass-related parameters, indicating potential multicollinearity and feature interaction effects. Additionally, the violin plot of average wet weight of vegetative growth (AWWVG) demonstrates both the distribution shape and density across classes, revealing multimodal patterns in some classes and clear separability in others, which is beneficial for classification tasks.

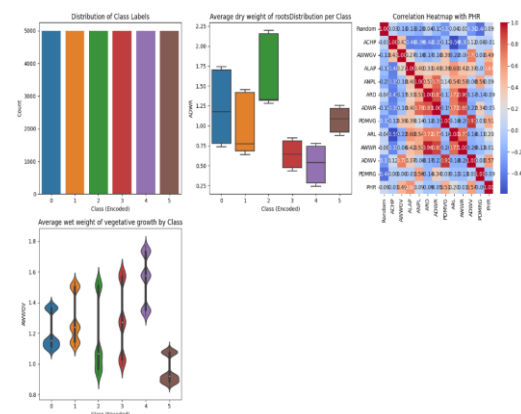


Fig. 4: EDA Plots of Research Work.

Fig. 5 presents the AUC-ROC curves obtained using (a) Existing SVC, (b) Existing BNB, (c) Existing MNB, and (d) Proposed DFPC model, illustrating the comparative classification performance across different approaches. The curves show that the proposed DFPC model achieves a superior trade-off between true positive rate and false positive rate, with a curve that consistently dominates the existing methods, indicating higher discriminative capability. In contrast, the existing SVC, BNB, and MNB models exhibit relatively lower curve elevations and reduced area under the curve,

reflecting comparatively weaker performance in distinguishing between classes.

Table 1 presents the performance comparison of classification models, including SVC, BNB, MNB, and the proposed DFPC model, evaluated using Accuracy, Precision, Recall, and F1-Score. Among the existing models, MNB achieves relatively better performance with an accuracy of 83.70%, precision of 85.05%, recall of 83.70%, and F1-score of 83.55%, followed by SVC with moderate results. In contrast, BNB shows significantly poor performance across all metrics, indicating its inability to effectively handle the dataset. The proposed DFPC model outperforms all existing approaches, achieving the highest accuracy of 94.42%, precision of 95.82%, recall of 94.42%, and F1-score of 94.26%. This substantial improvement highlights the robustness and superior classification capability of the DFPC model compared to traditional methods.

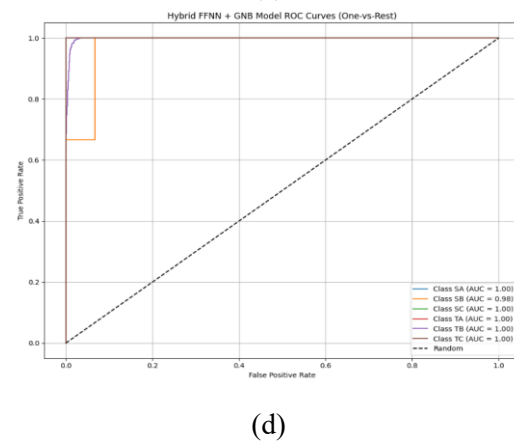
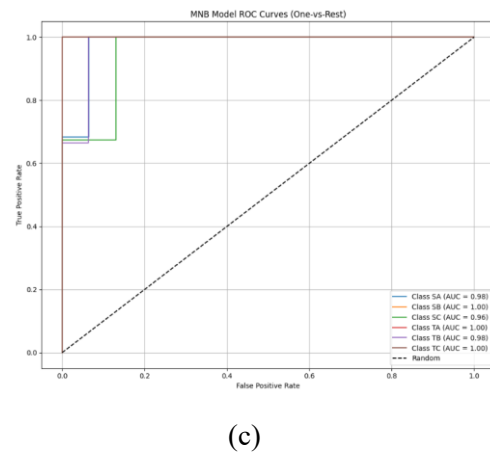
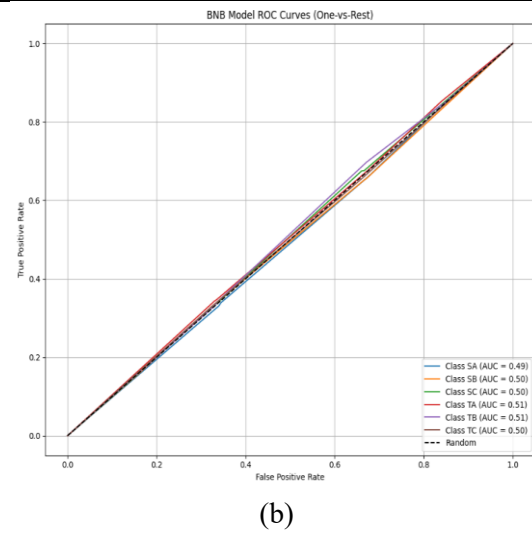
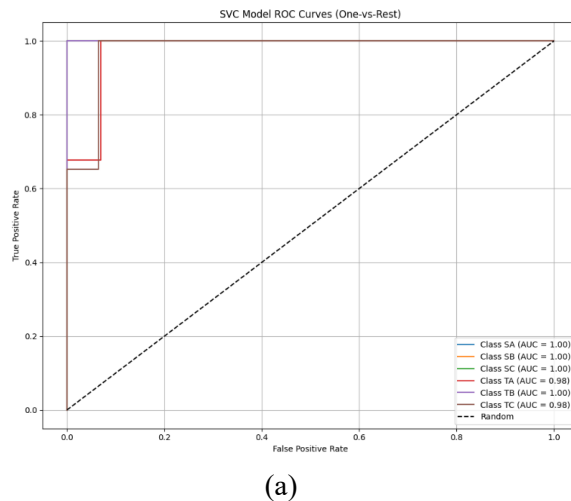


Fig. 5. AUC-ROC Curves obtained using (a) Existing SVC. (b) Existing BNB (c) Existing MNB (d) Proposed DFPC Model.

Table. 1: Performance comparison of classification models.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
SVC	77.92	80.70	77.92	77.60
BNB	16.53	5.54	16.53	8.09
MNB	83.70	85.05	83.70	83.55
DFPC	94.42	95.82	94.42	94.26

The comparative analysis of regression models shows in Table 2 noticeable differences in their ability to predict plant growth values from multi-sensor data. The DTR produced a mean absolute error of 6.77, mean squared error of 76.75, root mean squared error of 8.76, and an R^2 score of 0.459, indicating relatively low prediction accuracy. The SVR showed slightly improved performance with a mean absolute error of 6.31, mean squared error of 74.18, root mean squared error of 8.61, and an R^2 score of 0.477. The RR performed significantly better with a mean absolute error of 4.27, mean squared error of 38.39, root mean squared error of 6.20, and an R^2 score of 0.729. Among all models, the HDRP demonstrated the best performance with a very low mean absolute error of 0.22, mean squared error of 0.08, root mean squared error of 0.28, and an R^2 score of 0.999. These results indicate that the hybrid HDRP model provides highly accurate growth prediction by combining deep feature extraction with regularized regression analysis.

Table. 2: Performance comparison of regression models.

Model	MAE	MSE	RMSE	R^2 Score
DTR	6.77	76.75	8.76	0.459
SVR	6.31	74.18	8.61	0.477
RR	4.27	38.39	6.20	0.729

HDRP	0.22	0.08	0.28	0.999
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5. Conclusion

The study demonstrates an effective analytical framework for interpreting multi-sensor agricultural data to classify plant development stages and predict plant growth indicators in controlled environments. The implementation integrates data preprocessing, exploratory data analysis, and multiple machine learning models to analyse environmental sensor data. Experimental results show that the DFPC achieves the highest classification performance with an accuracy of 94.42%, outperforming traditional models such as SVC, BNB, and MNB. Similarly, for regression analysis, the HDRP produces highly accurate growth predictions with an R^2 score of 0.999, significantly improving prediction reliability compared to conventional regression models. The hybrid models enhance analytical performance by combining deep feature extraction with probabilistic and regularized learning techniques. These results indicate that integrating deep learning with classical machine learning algorithms can significantly improve predictive performance when analysing complex environmental datasets. The system can be enhanced to support real-time sensor data integration and cloud-based deployment for remote accessibility. Advanced deep learning models and automated hyperparameter tuning may also be introduced to further improve prediction accuracy and scalability.

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